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The Use of Modular Feed Forward Neural Networks in Anticipating the Results of Handball Championship 2015

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Abstract: Observation is a highly recommended approach in game analysis as it helps form a better understanding for the types of relations within the game. The aim of this study is to present a new approach for predicting competitions results which are based on game analysis by the use of Modular Forward Neural Networks (MFNN). The data of 80 games were analyzed (i.e. Fast break, Breakthrough, different type of shot…). The Data used to train Modular Feed Forward networks include 21 processing elements (PEs) as input, one element as output, 2 hidden layers, 100 epochs – termination Cross Validation, random initial weights, and weight update batch. The MFNN test contains single output case threshold 0, 5 on level 1000. Results show significant correlation between game results and neural network output 0.93, 0.96. Actual network output was 0, 91. Normalized Root Mean Square Error was 0,078. Final mean squared error was 0.9. The variables mostly affecting the results of (MFNN) were: fast breaks, and blocked shots. Using MFNN in predicting game results based on game details is considered a novel approach for evaluating the level of teams and competitors and for improving the training plans and tactics.

Keywords: Team Handball, Neural Networks, Anticipation

1. Introduction

During the last decade, it seems that the handball society has significantly benefited from game analysis through the regular and disciplined match analysis along with team-success determining factors of techniques, tactics and workouts. Monitoring rivals teams and evaluating them by various numeric values help re-arrange workouts. The game analysis studies in handball were classified into: Free analysis, acoustic analysis, written analysis, film analysis, video analysis, video/computer analysis and computer analysis [1]. Few literatures are interested in figuring out the relations between game details, as well as ways of investing the huge output numeric data in predicting game context. Research in game analysis has occupied a unique place in the field of sports science for a long time [2]; [3]; [4].

Neural Networks have been widely used in game analysis as they shed light on ways of using the data of game analysis effectively. Typical examples of this approach are tactical analysis and group behaviors [5]. Some literatures observed new approach of game analysis based on Custom Made Software (MASA) which is specific to determine players' positions based on tactical analysis [6] ; [7]. Other literatures studied the interaction between offensive and defensive group tactics [8].

Performance and results predictions were not challenging for specialists and if this challenge took place, specialists did not resort to the use of modern methods such as advanced nonlinear modeling techniques [9] ; [10]. A substantial amount of exertion should be spent on foreseeing the results of sporting events [11]. Other researcher assumed that utilizing the neural systems helps rate and select particular players for specific rivals [12] ; [13].

From this point of view the previous literatures did not pay attention to observed methods of predicting games results based on previous analytical data from game context. Therefore the aim of this study is to give new methods for anticipating game championship results by means of Modular Feed Forward Neural Networks.

The Modular Feed Forward Neural Networks (MFNN)

MFNN is considered a special class of a multilayer perceptron (MLP), which processes the input by utilizing a few parallel MLPs, and recombines the outcomes. This has a tendency to make some structures inside of the topology cultivate specialization of capacity in every sub-module. As opposed to the MLP, particular systems don't have a full interconnectivity between their layers. Thus, a fewer number of weights are needed for the same size system (i.e. the same number of PEs). This has a tendency to accelerate preparing times and to diminish the quantity of obliged preparing models. There are numerous approaches to portion an MLP into the module. It is hazy how to plan the measured topology in light of the information. It cannot be certain that every module is practicing its preparation for a one of a kind part of the data [14];[15].

2. Material & Methods

Out of 160 half games from the handball world cup championship 2015, 149 half games were analyzed, the only half - games finished with a win or lose were considered, no equal games are included in this study. Eighteen quantity / quality game variables were determined as shown in table (1).

Table 1. *Quantity / Quality game variables and desired results of half games for each team.*

Input Data																			**Desired Data**	
Team	**Total Shot**	**6M Goal**	**6M Shot**	**Wing Shot Goal**	**Wing Shot**	**9M Goal**	**9M Shot**	**7M Goal**	**7M Shot**	**Fast Break Goal**	**Fast Break shot**	**Breakthroughs Goal**	**Breakthroughs Shot**	**Assists**	**Technical Fault**	**Steals**	**Blocked Shots**	**2 Minute Suspensions**	**Lose**	**Win**
ALG	331	29	43	26	44	42	156	18	26	32	45	15	17	87	89	36	12	20	*9*	*1*
ARG	266	30	50	26	35	34	90	17	26	26	36	19	29	75	79	30	11	20	*5*	*6*
AUT	296	24	41	25	43	41	96	16	20	48	69	20	27	92	78	31	16	20	*6*	*4*
BIH	320	51	77	16	35	44	116	16	26	30	40	18	26	103	102	32	17	21	*8*	*2*
BLR	355	72	114	27	40	34	104	18	24	37	43	27	30	103	99	28	15	22	*7*	*3*
BRA	307	40	73	17	29	35	109	15	19	38	48	26	29	86	88	33	6	18	*8*	*4*
CHI	321	45	75	8	22	33	122	25	36	25	32	29	34	74	117	32	11	20	*7*	*3*
CRO	410	38	56	37	55	78	174	29	39	56	64	20	22	116	109	39	42	26	*5*	*13*
CZE	348	22	38	22	40	55	130	27	34	62	76	21	30	111	89	30	30	22	*6*	*4*
DEN	413	73	102	32	38	80	169	23	27	46	54	18	23	152	92	23	29	28	*2*	*12*
EGY	271	24	47	17	32	49	111	18	27	17	22	26	32	63	63	25	16	18	*6*	*4*
ESP	419	61	78	40	54	60	155	31	41	49	60	24	31	151	119	38	42	26	*3*	*13*
FRA	413	53	81	34	48	50	132	40	48	44	58	38	46	131	94	52	32	26	*3*	*14*
GER	386	58	86	28	39	45	116	28	38	56	67	35	40	138	105	29	35	30	*6*	*10*
IRI	358	36	53	17	29	65	186	17	25	37	49	13	16	91	115	30	17	16	*8*	*1*
ISL	296	28	45	24	39	49	139	14	18	27	36	10	19	93	52	22	12	18	*7*	*4*
KSA	333	24	46	10	32	40	170	12	21	30	38	20	26	51	118	30	8	21	*10*	*0*
MKD	284	40	53	29	39	42	103	23	31	31	41	16	17	109	65	16	10	18	*4*	*7*
POL	404	66	92	21	30	68	170	17	26	43	53	26	33	112	117	48	31	30	*8*	*9*
QAT	426	75	113	10	20	75	195	26	33	22	25	37	40	114	105	38	9	25	*8*	*10*
RUS	339	33	53	31	51	54	128	23	29	43	50	21	28	97	86	31	18	17	*5*	*5*
SLO	417	50	77	36	54	35	99	32	40	64	81	56	66	149	122	39	33	29	*10*	*8*
SWE	261	31	38	14	29	44	107	19	23	36	43	13	21	102	80	29	22	18	*2*	*8*
TUN	292	40	64	19	32	43	123	11	20	23	31	16	22	69	54	21	5	19	*6*	*4*

Network Design, Training and Test

The network design and training procedures contain 21 PEs as input, one as output, sixteen exemplars, two hidden layers, 100 Epochs Termination Cross Validation, random initial weights and weight update batch. The MFNN test contains single output case threshold 0.5 on level 1000 Epochs (as shown in fig 1).

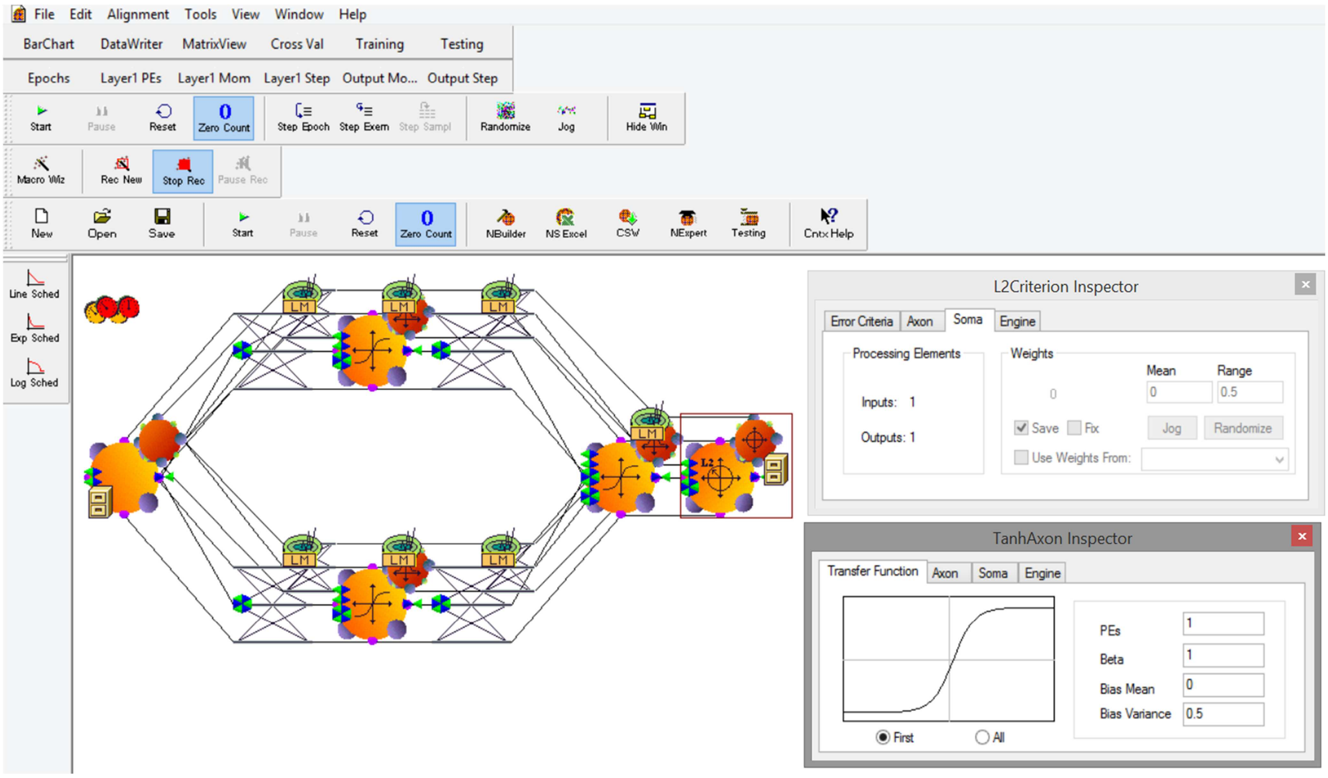

Figure 1. *Graphical user interface of the (MFNN).*

The outputs of championship analysis (eighteen quantity / quality variables) were used to feed the neural network as input data, also game results (win / lose) were marked as desired data. Up to 70% of all data were marked as training, while 15% were marked as cross validation. Cross validation processes the lapse in a test set while the system is being prepared with the preparation set. It is realized that the mean squared normalized error (MSE) will continue to diminish in the preparation set, however, it may begin to increase in the test set. This happens when the system begins "remembering" the preparation designs. The Termination page of the enactment control reviewer can be utilized to screen the cross approval set mistake and consequently it stops the system when it is not progressing. 15 % of all data were marked as testing data. The sufficient correlation between desired and output results from the neural network was calculated. The network train report also contains minimum training MSE at last epoch (table. 2).

Table 2. *Mean squared normalized error for training and cross validation.*

Best Networks	Training	Cross Validation
Epoch #	8	1
Minimum MSE	5.74129E-29	0.022651597
Final MSE	5.74129E-29	0.053782498

3. Results

There is no significant different between the mean of actual championship results and the MFNN results. P value was 0.005 in case of win or lose as show in table 3.

Table 3. *The mean and standard deviation of actual and (MFNN) output data, P values (2-tailed test) also shown.*

Half games	Actual data		Network output		P
	Mean	SD	Mean	SD	
Win	6,2	1.1	5.58	0.97	0.005
Lose	6,2	1.1	5.76	0.99	0.005

Test report on network performance shows values of Root Mean Square Error (RMSE), it was between 2.5 in case of win and 2.3 in case of lose. Normalized Root Mean Square Error (NRMSE) and Mean Absolute Error (MAE) are also shown. Correlation between the actual results and the MFNN results was very high. In case of win, it was 0.930 and in case of lose, it was 0.960 as shown in table 4.

Table 4. *The test report error of the neural network shows the sufficient correlation between desired competition results (win / lose in each half game) and (MFNN) output data.*

Performance	Win	Lose
RMSE	2.517	2.316
NRMSE	0.209	0.217
MAE	2.272	2.649
Min ABS Error	0.180	0.183
Max ABS Error	3.382	3.303
R	0.930	0.960

The accuracy of actual competition results and the MFNN output are shown in fig 2 and the game data affecting the MFNN accuracy are shown in fig 3.

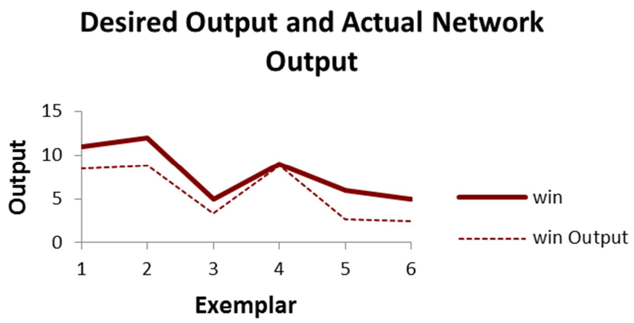

Figure 2. *Championship game results and actual (MFNN) output. (I.e. Win for each half game)*

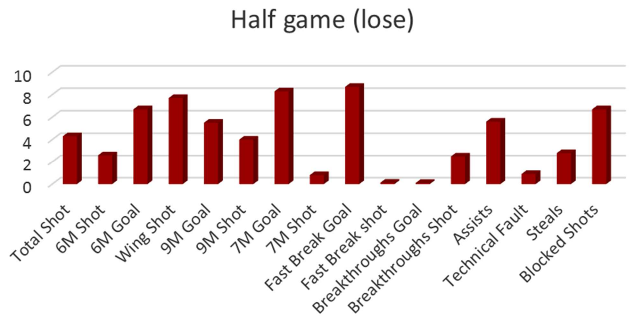

Figure 3. *The Data of Half Game (Lose) Affecting (MFNN) output.*

4. Discussion

The previous presentation of the results shows the reliability of the MFNN methodology in predicting the results of games in the competition. Previous studies relied on the prediction of athletic performance only without the possibility of pre-research to identify the results of matches, therefore, they used a hybrid prediction system based on genetic algorithm and artificial neural network (GANN) [12], or the neural networks to select players. Both are based on tests in advance [13].

This study tried to anticipate the results of the handball world cup championship 2015 by using modular feed forward neural networks and relied on neural network feed variables resulting from the analysis of the tournament and number 18 variables from game events, The results show that there are no significant differences between the expected output of the MFNN and the actual data of the competitions. Results also showed the presence of a high correlation between the output results by using MFNN and actual results for each half game in all cases of winning and losing as 93% and 96%, respectively.

Also, the mean square error of the neural network was at its lowest value 1.8, which increased the confidence in the results presented. In the same context, the sensitivity of MFNN input data to game (win/lose) will help trainers and experts to understand the nature of the biggest factors influencing the outcome of matches and thus they work to take advantage of playing through the development of training programs and plans. Another point of view adopts the possibility of the use of MFNN to evaluate team performance in a phased manner during the competitions. It will identify the level at which the team is heading and its competitors. This will help us make quick decisions that will change the course of the results and the team.

The prospective values of this study is to show that the approach of artificial Feed Forward Neural network dealing with the methods of optimal use of the data in the field of sports based on performance analysis is a reliable approach in predicting game results. The performance output data are necessary as a base to predict other values in cooperation with MFNN. Using this proposed methodology of MFNN helps predict large values which in turn will lead us to improve the player's performance, (I. e.) Type of tactics.

5. Conclusion and Future Work

The Modular Forward Neural Network was used for game execution forecast. The test results can help the trainers to nearly foresee the performance of the team and the competitors. Any future research work ought to look at some genuine information from distinctive games and diverse levels. Moreover, the researchers ought to enhance the calculation to make the expectation more exact. At long last, it ought to look at different methodologies for expectations.

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